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Diagnostic accuracy of audio-based seizure detection in patients with severe epilepsy and an intellectual disability

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ABSTRACT

We evaluated the performance of audio-based detection of major seizures (tonic–clonic and long generalized tonic) in adult patients with intellectual disability living in an institute for residential care.

Methods: First, we checked in a random sample (n = 17, 102 major seizures) how many patients have recognizable sounds during these seizures. In the second part of this trial, we followed 10 patients (who had major seizures with recognizable sounds) during four weeks with an acoustic monitoring system developed by CLB ('CLB-monitor') and video camera. In week 1, we adapted the sound detection threshold until, per night, a maximum of 20 sounds was found. During weeks 2–4, we selected the epilepsy-related sounds and performed independent video verification and labeling ('snoring', 'laryngeal contraction') of the seizures. The video images were also fully screened for false negatives. In the third part, algorithms in the CLB-monitor detected one specific sound (sleep-related snoring) to illustrate the value of automatic sound recognition.

Results: Part 1: recognizable sounds (louder than whispering) occurred in 23 (51%) of the 45 major seizures, 20 seizures (45%) were below this threshold, and 2 (4%) were without any sound. Part 2: in the follow-up group (n = 10, 112 major seizures; mean: 11.2, range: 1–30), we found a mean sensitivity of 0.81 (range: 0.33–1.00) and a mean positive predictive value of 0.40 (range: 0.06–1.00). All false positive alarms (mean value: 1.29 per night) were due to minor seizures. We missed 4 seizures (3%) because of lack of sound and 10 (9%) because of sounds below the system threshold. Part 3: the machine-learning algorithms in the CLB-monitor resulted in an overall accuracy for 'snoring' of 98.3%.

Conclusions: Audio detection of major seizures is possible in half of the patients. Lower sound detection thresholds may increase the proportion of suitable candidates. Human selection of seizure-related sounds has a high sensitivity and moderate positive predictive value because of minor seizures which do not need intervention. Algorithms in the CLB-monitor detect seizure-related sounds and may be used alone or in multimodal systems.

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1. Introduction

Nocturnal seizures often go unnoticed and are associated with SUDEP [1]. For detection of these seizures, heart rate [2–4] and movement [5] are the physical signs most often used. Audio detection has become popular in many fields of health care, because it only uses the traditional acoustic monitoring systems for night-care and is a non-intrusive method. Until now, audio-based detection of epileptic seizures has been disappointing because of the plethora of noise that is received during the night in many hospitals. Audio-based seizure detection, however, remains attractive, because some of the patients have specific seizure-related sounds, which easily can be identified by the human ear if heard in situations where only a few sounds are passed though the widely used audio-based surveillance systems.

In a previous study [6] in our institute, automatic detection of a number of specific sounds (by matching their frequency spectrum) resulted in high performances. However, we still do not know what the audio detection will miss or detect falsely, because of lack of sounds, minor epileptic seizures such as myoclonic or short tonic seizures (which do not need intervention), or nonepileptic events.

Therefore, we studied the usefulness of audio-based nocturnal seizure detection in patients with severe epilepsy in a residential setting with video as the gold standard. All of the patients were adults with an intellectual disability and had been previously studied by EEG/video.

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The STARD criteria [7] and ILAE classification of 2010 [8] were used. To assess the representativeness of our study population, we present an earlier trial in which we assessed the prevalence of sounds in a broader population of adults having an intellectual disability. Finally, to check the potential value of completely automatic sound recognition, we analyzed the performance of automatic analysis of 'snoring' sounds.

2. Methods

The research received prior approval by the institutional review body of Kempenhaeghe, and informed consent was obtained from each patient's representative. In Kempenhaeghe, we run a continuous program for seizure detection investigating 40–50 patients each year. The 17 initial subjects in Section 2.1 entered our program in 2008, while the 10 subjects investigated in Section 2.2 were consecutively selected during 2014.

We followed a stepped approach in our in-hospital population of patients with intellectual disability and severe epilepsy.

2.1. Representativeness check

To assess the representativeness of our study population, we determined the proportion of patients that produced sounds during their major seizures: generalized tonic–clonic (>30 s) or generalized tonic seizures of long duration (>30 s). In 17 patients, 102 major seizures occurred during 4 weeks. Forty-five seizures were classified as major motor seizures (tonic–clonic or long generalized tonic seizures). All other (nonmajor) seizures (50) were labeled as minor seizures, and 7 could not be classified (not included in the analysis). The perceived loudness of the seizure sounds was subjectively judged by a panel (PvM and JA) on a relative scale of loudness (0–100% in steps of 10%). We used the following loudness reference sounds: whispering (20–30% of the scale), talking (40–60%), and screaming (70–90%). The panel concentrated during the trial on the sounds and was not looking at the video, but they were not completely blinded; in a later stage, the video was scored by the same panel.

2.2. Human sound recognition and analysis

From the population of 284 patients with intellectual disability and severe epilepsy, we randomly selected 10 patients (12–65 years old) who were known to make audible sounds during their seizures and suffer at least one major seizure a week. The patients were diagnosed during our clinical seizure detection program where seizures were detected during a clinical study of 1 week (2 days EEG/video followed by 5 days video and multimodal non-EEG sensors for accelerometry and heart rate which were not used in this study). During the trial period, we used the threshold-based CLB-monitor to collect sounds with simultaneous continuously recorded nocturnal video monitoring during 4 weeks. In the first week, we collected noise fragments with a sound pressure level above a predefined threshold. This threshold was set manually per patient, varying from a level corresponding to whispering, up to a level corresponding to shouting. The integration times used for each patient varied in the range 0.0 to 2.5 s. Furthermore, we identified sounds that were specifically related to the videotaped epileptic seizures (for example, due to laryngeal spasm, a myoclonic hiccup, coughing). During the first week, the audio threshold was adapted until, per night, a maximum of 20 sounds were above the threshold. Generally, between 2 and 20 sounds were detected by the system, of which 0–2 could be linked to epileptic seizures (0–10% of unselected sounds). During the following 3 weeks, all sounds were collected and classified as belonging to seizures or not. Afterwards, the relation of the presumed seizure-related sounds to the real seizures was independently verified (by video), the seizures were classified, and the nature of the sounds labeled. To avoid missed seizures, all video recordings were screened for each night (at 16× normal speed). When doubtful episodes were suspected at high speed, we went back to a normal speed for a period of 5 min around the event. Suspected or possible seizures were classified by a panel (one epileptologist and at least two nurses specializing in epileptology). The sensitivity and positive predictive value of the seizure-related sounds for the detection of major seizures were determined. Furthermore, the number of false sound alarms per night was assessed.

2.3. Automatic sound selection

An automated sound event detection system by Sound Intelligence was tested on the collected audio data as well. The system is based on machine learning, making it necessary to have sufficient amounts of data for a particular sound category in order to be able to train and test the system. Depending on the sound class, a specific combination of decision tree algorithms and/or neural network algorithms is chosen to achieve optimal results. In the data collected in this trial, not enough epilepsy-related sounds were collected, making it impossible to train the system on these categories. However, sufficient data were available for 'snoring' (including sleep-related snoring), which was the most prominent sound in three patients (see Results, Table 2). For these patients, a snoring detector would be relevant in detecting seizures.

The machine learning algorithm used consisted of a neural network and was trained and tested only for snoring, as a proof of concept for detecting other types of epilepsy-related sounds in the future, once sufficient amounts of epilepsy-related sounds have been collected. To train and test the SI-monitor, the available audio data were annotated manually and split randomly (not by patient) in training and validation sets using a 70/30 ratio. This resulted in a training set consisting of 3760 events (of which, 936 were annotated as 'snoring') and a validation set consisting of 1608 events (of which, 338 were annotated as 'snoring'). The system was trained to classify snoring and classify all other sounds just as 'other'. After training, the system was validated using the validation set.

Because this was a diagnostic study, only descriptive statistics are presented.

3. Results

3.1. Representativeness check

Results of the perceived loudness of the seizure sounds are depicted in Fig. 1.

At least one sound event was found in 60 of the 95 seizures (63%), in 43 of the 45 major seizures (96%), and in 17 of the 50 other minor seizures (34%). Recognizable sounds with a perceived loudness above the level of whispering occurred in 23 (51%) of the major and 6 (12%) of the minor seizures.

In other words, 96% of major seizures were accompanied by sound, of which about half had a sound perception level (SPL) above the detection threshold (whispering). Only 34% of the minor motor seizures were accompanied by sound, of which only 12% had an SPL above the detection level.

The types of the sounds are depicted in Fig. 2.

From this figure, one can see that screaming and bed sounds are predominantly related to major seizures.

3.2. Human sound recognition and analysis in our selected patient population

The mean age of the patients was 34 years (range: 18–42 years); 6 patients were female, and 4 were male. All patients were known to suffer from symptomatic generalized or multifocal epilepsies and had a moderate-to-severe intellectual disability. In Table 1, the results of the manual audio analysis are shown. From this table, it is obvious that manual selection of seizure-related sounds is a sensitive procedure. False alarms are related to less severe, minor seizures that do not require an intervention. In Table 2, the most frequent types of seizure-related sounds

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